

# Genetic Algorithm Optimization of Inlet Geometry for a Hypersonic Jet Engine with Mode Transition

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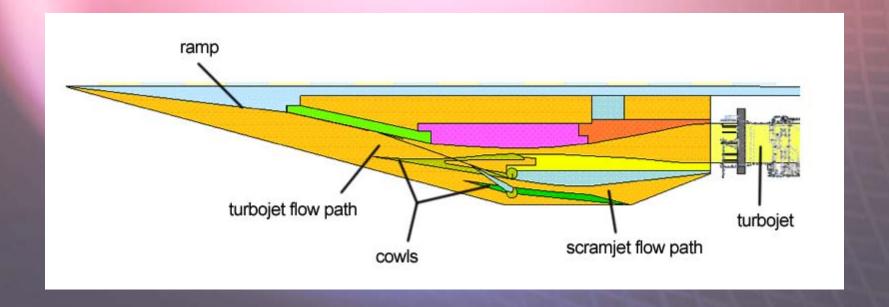
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#### Introduction

- The role of computational fluid dynamics (CFD) and optimization through CFD
  - Simulation data helps to focus experiments.
  - Reduce wind tunnel expenses
- The promise of genetic algorithm optimization
  - "natural selection" in a "population" of designs
  - Selection takes care of design process → little knowledge required
  - Multiple designs in a population → parallel computing

#### Introduction

- Baseline design for this GA optimization
  - The Large-scale Inlet Mode Transition (L/IMX) inlet
  - The need for transitional inlets on high-Mach aircraft

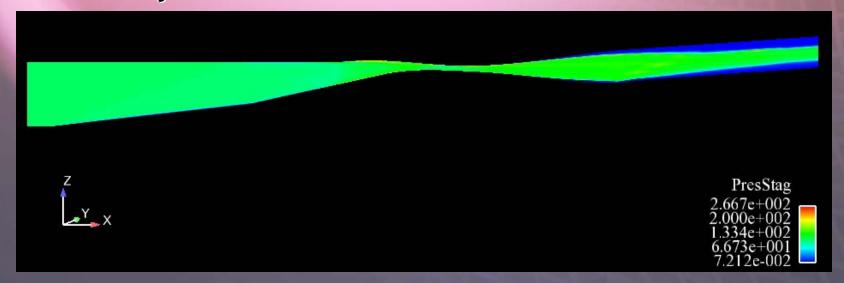


#### Problem Definition

- Optimize inlet's contribution to the efficiency of the engine
- Significance of total pressure for efficiency
  - a.k.a stagnation pressure
  - Decreases with entropy generation
  - Reflects flow's ability to do work
  - Total pressure recovery = p<sub>t, exit</sub> / p<sub>t, entrance</sub>
- Concerns:
  - The shock train → shock losses
  - Boundary layers → entropy, more shock loss

# Objective

- "Implement a GA to design an optimum geometry for the turbojet flow path of a hypersonic jet engine inlet at Mach 4, using the L/IMX inlet as a baseline."
- Mach 4 = cutoff for turbojet
- Optimum = highest possible total pressure recovery
- Non-uniform flow at exit → use average total pressure recovery over cross-section

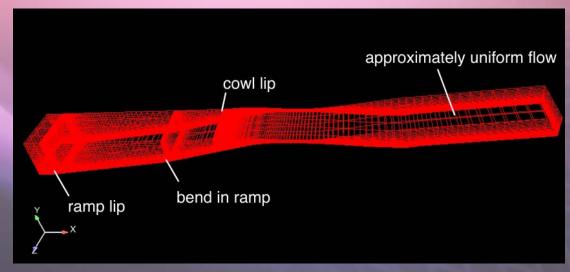


### Approach

- Define and implement key components of the GA
  - + Alleles
  - Chromosomes
  - Fitness
  - Initialization
  - Parent selection
  - Crossover
  - Mutation
  - Elitism
  - Design constraints
- Validate the GA through tests
- Lay out how the GA interacts with auxiliary programs, data files, and scripts

### Approach: Alleles

- Definition: design parameter values that define an individual
- 25 total, 3 types:
  - Coordinates of key points along the inlet
  - Bias values: which way does the wall bend?
  - Tightness values: how sharply does it bend?



### Approach: Chromosomes

- Definition: a list of an individual's alleles
- Alleles are listen in order of type:
  - X-coordinate of cowl lip
  - Y-coordinates of all key points (x fixed)
  - Bias values
  - Tightness values

### Approach: Initialization

- Definition: the generation of an initial population
- Initial population generator (IPG) separate from GA
- Individuals distributed randomly in design space
  - Uniform probability for all possibilities, each allele
- L/IMX design always included

### Approach: Fitness

- Definition: the cross-sectional average total pressure recovery
- CFD output (density, velocity) → total pressure
- CFD output is nondimensional
- Accommodating non-uniform exit flow
  - CFD results only at discrete grid points
  - Riemann sum, divide by area → p<sub>t, exit</sub> , p<sub>t, entrance</sub>
  - Total pressure recovery = p<sub>t, exit</sub> / p<sub>t, entrance</sub>

### Approach: Parent Selection

- Definition: selection of individuals to pass on their alleles to the next generation
- Check: 2 unique parents for crossover
- Higher fitness -> more likely to be chosen
- Roulette Wheel
  - Individual's "wedge on the wheel" proportional to fitness
  - "roulette ball" stops at a random point around the wheel

# Approach: Crossover

- Definition: 2 parent chromosomes swap or blend alleles to form 2 children
- Occurs with 70% probability
- If crossover, then for each allele, numbered 1-25:
  - 1/3 chance alleles remain unchanged
  - 1/3 chance alleles swapped between parents
  - 1/3 chance blended crossover
- Blended crossover
  - Children's alleles = randomly weighted averages of parents

$$a_{child1} = \gamma a_{parent1} + (1 - \gamma) a_{parent2}$$

$$a_{child2} = \gamma a_{parent2} + (1 - \gamma) a_{parent1}$$

### Approach: Mutation

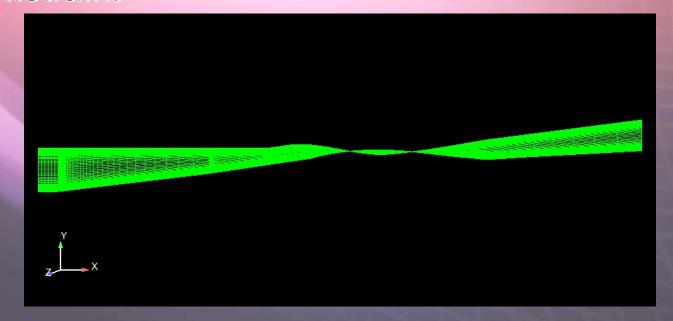
- Definition: a random allele changes its value
- Occurs for every new individual except the one copied through elitism
- One allele chosen at random per individual
- Allele value changes to any value in design space
- Uniform probability of all possibilities

### Approach: Elitism

- Definition: automatically copy the individual with the highest fitness is into the nest generation
- The only exception to crossover and mutation
- The best fitness cannot decrease over generations.
- Speeds convergence
  - Favors high fitness
  - May converge too soon for small populations

# Approach: Design Constraints

- The inlet walls cannot intersect
- The cowl lip must be upstream of the shock off the ramp
- Retry generating the individual if it violates a constraint



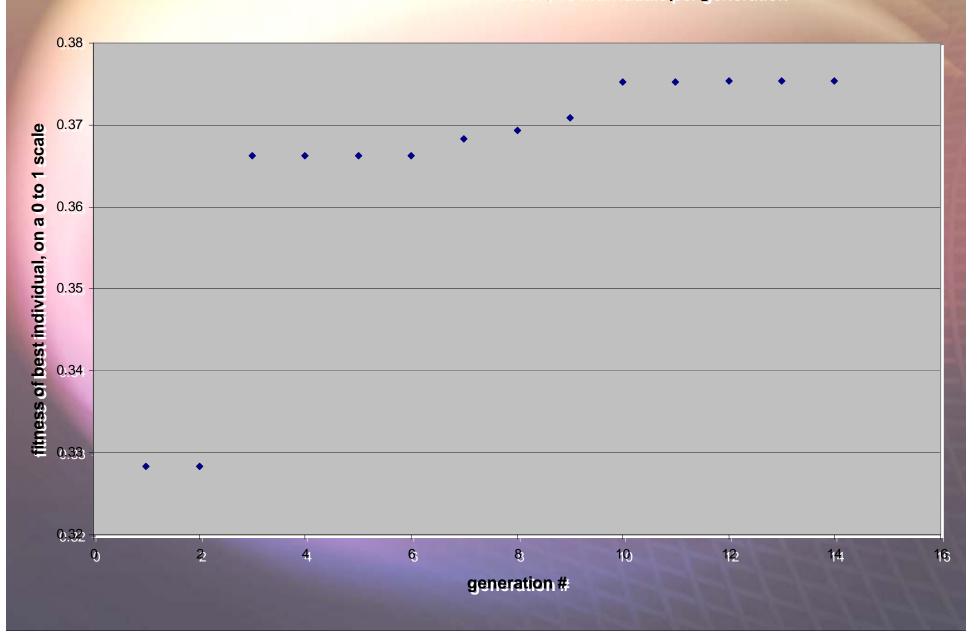
### Approach: Validation

- Use dummy fitness function to test GA performance
- Dummy fitness function:

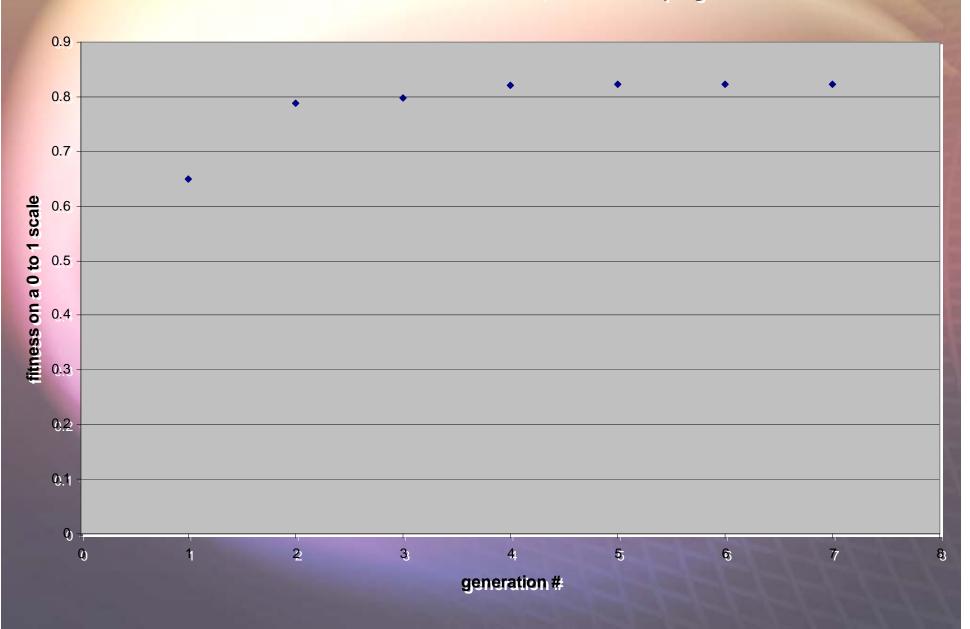
$$f(x) = |\cos((x-400)/25) * e^{-|(x-400)/400|}|$$

- x = sum of allele values
- Resulting changes for improvement:
  - Don't have all designs on one side of optimum
  - Give initial population uniform probability across design space
  - Give mutation uniform probability across design space
  - Increase mutation to 100% probability of occurrence

#### Fitness of Best Individual in Each Generation, 10 individuals per generation



#### Fitness of Best Individual in each Generation, 10 individuals per generation



### Approach: Validation

- Use L/IMX inlet to test actual fitness calculations
- After debugging, total pressure recovery = 0.4377
- Resulting changes for improvement:
  - gridline distribution function from grid generator -> average by area
  - Read from binary result file, not ASCII

# Approach: Analysis Tools

#### Overflow

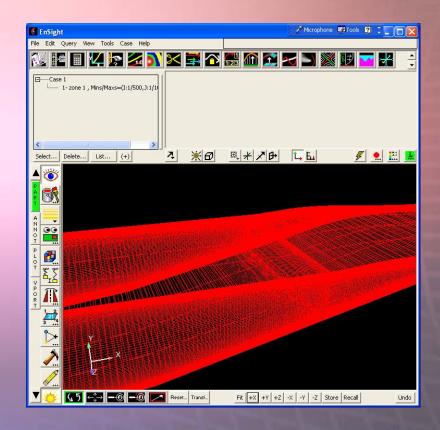
- CFD software, calculates flow behavior
- Input: Plot3D grid, boundary conditions, "restart" options
- Output: density, velocity vectors at gridline intersections
- Boundary conditions: inviscid approaching inlet, viscid inlet walls

### Approach: Analysis Tools

- Grid generation
  - GA outputs 2D grid file
  - "makegrid" script converts to nominally
     3D file for Overflow
  - Grid concentration near walls, ramp corners, cowl lip

# Approach: Analysis Tools

- EnSight
  - Visualizes grid files,
     Overflow result files
  - Color codes
     according to flow
     properties
     (temperature, Mach,
     pressure, etc.)



#### Approach: Program Interaction

- Programs and files across2 machines
  - Columbia, NASA supercomputer at Ames
  - Lou, NASA mass storage machine
- Batch script calls:
  - IPG to begin
  - GA for each generation
  - moves files as needed.

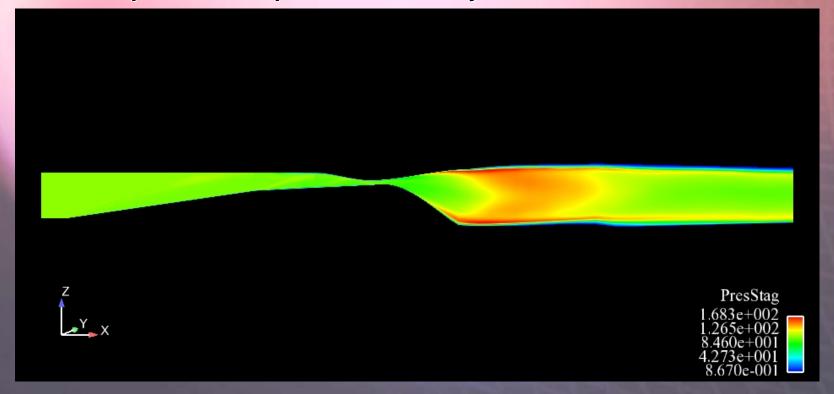
- Columbia stores executables
  - + GA
  - + IPG
  - Overflow
  - Scripts
- Lou stores archives
  - grid files
  - Chromosomes
  - Fitnesses
  - best scores

#### Results

- Functional Initial Population Generator (IPG)
  - Well distributed across design space
  - Avoids constraint violations
- Functional fitness calculation
- Functional random number generator
  - Does not repeat between runs of the program
  - Does not repeat when called repeatedly in program
- Functional GA
  - Fitness improves from baseline and never backslides
  - Performance improves with larger populations, but computing time limited for this project
  - Avoids constraint violations
  - Well-tested grid generation

#### Results

- Improved design from small-scale run
  - Total pressure recovery of baseline = 0.4377
  - Improved total pressure recovery = 0.4450



#### **Future Work**

- Improved compatibility with Columbia
- Run large-population, many-generation cases
  - Possibly multiple days each to run on Columbia
  - Generations of >100 individuals
  - Thoroughly explore design space
- Tweak GA to improve efficiency
  - Alternate parent selection methods
  - Crossover, mutation probabilities
  - Alternate crossover, mutation setup
- Tweak constraints, coordinating with L/IMX

#### Conclusions

#### Pros of GA Approach

 GAs explore parts of design space far from baseline

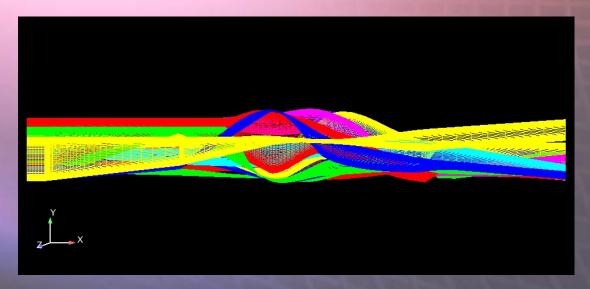
Multiple designs to test →

Parallel (efficient) computing

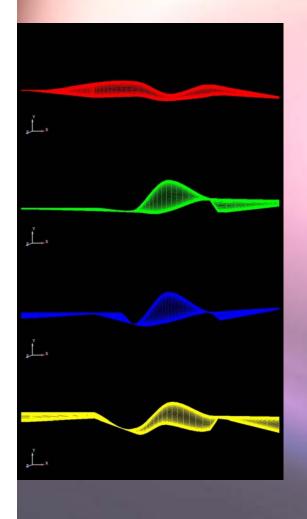
adaptable

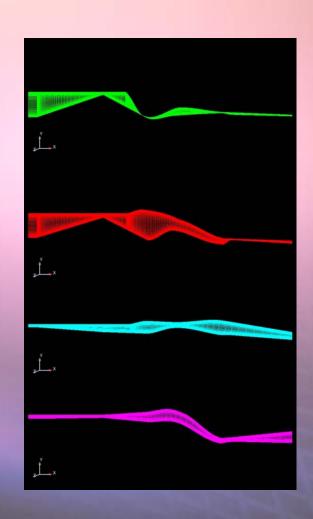
#### Cons of GA Approach

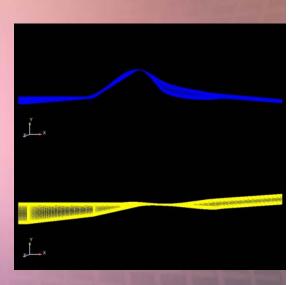
- Requires great (expensive) computational power
- Requires extensive computing time



#### Conclusions







#### Acknowledgements

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